Cooperation in a Fragmented Parliament: Analyzing Voting Agreement Among Dutch Political Parties

A Pre-Election and Post Coalition Formation Social Network Analysis of Parliamentary Voting in the Netherlands (2023–2024)

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Table of contents

Abstract

The increasing fragmentation of the Dutch party system has complicated stable coalition formation and raised questions about how political parties cooperate in everyday parliamentary practice. This study contributes to existing work by analysing how parties collaborate through agreement on motions during the 2023-2024 electoral cycle, treating these patterns as a network and examining their structure. Two research questions guide the analysis.

First, we ask whether patterns of voting agreement differ between the year preceding the 2023 elections and the year following coalition formation (RQ1).

Second, we examine whether voting agreement is shaped by ideological similarity, shared coalition experience, co-sponsorship of motions, and endogenous network structures (RQ2).

The study constructs weighted party co-voting networks and applies a Quadratic Assignment Procedure (QAP) to compare network structures across periods. Exponential Random Graph Models (ERGMs) on binarized weighted networks are used to explain voting agreement behavior for each period. The QAP results show no significant correlation between the pre-election and post-formation networks, indicating a change in cooperation patterns between the two time frames. The ERGM results show that ideological similarity does not affect voting agreement before elections but becomes a significant predictor after coalition formation. Co-sponsorship on writing motions has a modest positive effect in both periods, while shared coalition experience does not significantly increase agreement. Both studies combined provide unique insights in Dutch parliamentary cooperation patterns.

1 Introduction

Over the past decades, the Dutch political landscape has become increasingly fragmented. Of the 54 registered parties, 15 currently hold seats in the House of Representatives. This large number of parties and the resulting fragmentation hinders formation of stable majority coalitions (Otjes & Louwerse, 2015a). The repeated government falls since 2017 underline this structural tension: as the number of viable parties grows, ideological distances widen, further complicating coalition formation and stability (Schmitt, 2016). In such a fragmented setting, understanding how parties actually collaborate requires looking beyond formal coalitions to their everyday behaviour in parliament.

This study therefore examines parties' voting behaviour on parliamentary motions[1], focusing on voting agreement. Voting agreement refers to the extent to which two parties cast the same vote, either both in favour or both against, on the same motions. Because voting in the Dutch parliament takes place at the party level, these patterns provide a direct behavioural indicator of how close parties align in practice. Measuring and explaining voting agreement helps reveal which factors are most important for forming cooperative and stable coalitions. The study focuses on the 2023-2024 parliamentary cycle, using social

[1]Motions are statements from the Dutch House of Representatives or the Senate, proposed by one or more members of parliament. A motion can cover various topics, such as responses to new developments, policy attention for specific topics, or requests for funding adjustments (Parlement.com, n.d.b).

network analysis to explore how parties vote together and the factors shaping this behaviour through two complementary studies.

1.1 Study 1

Previous studies show that parliamentary voting adapts to political context. For instance, Lami et al. (2014) found that party alignment in Italy changed after government transitions. Because party alignment in parliament can be expressed through how parties vote on the same motions, changes in political context should be observable as changes in voting agreement between parties. Hence, to investigate whether such patterns occur in the Netherlands, Study 1 examines whether voting agreement changes between (a) the year before the 2023 elections and (b) the year after coalition formation. It addresses the following research question:

> RQ1: Do Dutch political parties show different patterns in voting agreement with respect to motions in the period before elections compared to the period after coalition formation?

Louwerse et al. (2017) demonstrated that cross-party support tends to decline during election campaigns but intensifies after the formation of a new coalition. Together with the findings from Lami et al. (2014) this presents that shifts in political context can lead to different voting behavior. Therefore, the hypothesis for this research question is the following:

> H1.1: Dutch political parties show different patterns of voting agreement in the period before elections compared to the period after coalition formation.

To test the first hypothesis, two networks will be created: one for the period before the elections and one for the period after the coalition formation. These networks are described in more detail in Section 2. They will be compared using a Quadratic Assignment Procedure (QAP) correlation test.

1.2 Study 2

Voting agreement between parties is influenced by multiple factors. Research shows collaboration is shaped by ideological proximity, institutional cooperation, and inter-party voting dynamics (Fowler, 2006; Shiraito et al., 2023). Parties with similar views tend to take similar positions, parties that have governed together often continue to cooperate, and broader voting patterns also shape agreement.

Building on these insights, Study 2 examines the factors driving voting agreement between Dutch parties for both networks from Study 1. The research question is:

> RQ2: How do ideological similarity, shared coalition experience, and structural voting patterns influence inter-party agreement on parliamentary motions?

The ideology of a political party reflects its core beliefs and values about how society should function (Corcoran et al., 2020). It is typically measured on a left-right axis, though this may not fully capture political orientation (Van Erkel & Turkenburg, 2022), leading to proposals for a bi-dimensional approach (Boräng et al., 2024). In the Dutch context, a second cultural progressive-conservative dimension is recognized. Despite this, cultural issues also influence left-right positions (De Vries et al., 2013), suggesting the two dimensions may be too closely intertwined (see Appendix A for empirical validation). Therefore, this research considers only the left-right axis for its first hypothesis:

> H2.1: Parties with similar ideologies on the left-right spectrum are more likely to agree on motions.

Coalition formation is essential for government formation, requiring parties to reach agreements for effective policy-making. Research shows that these agreements are effectively enforced in the Netherlands (Moury & Timmermans, 2013) and help parties coordinate on policy reforms (Bergman et al., 2023). Furthermore, coalition experience reduces affective polarization in public opinion (Hahm et al., 2024) and may similarly strengthen trust and coordination at the parliamentary level. Hence, the following hypothesis is proposed:

> H2.2: Parties that have often been in a coalition together are more likely to agree on motions.

Motions are frequently created by several MP's working in conjunction together, an approach called co-sponsorship. MP's introduce resolutions and amendments across party boundaries with those MP's who specialize in similar topics (Otjes & Louwerse, 2015a). MP's frequently tend to co-sponsor bills to signal approval for a motion (Kessler & Krehbiel, 1996), which can originate from coalition membership as well as ideological similarity (Otjes & Louwerse, 2015a). Since voting unity within parties is almost 100% in Dutch politics (Andeweg & Irwin, 2009), co-sponsorship behaviour at MP level can be abstracted to the party level and results in the following hypothesis:

> H2.3: Parties who frequently co-sponsor motions tend to agree more with each other.

There are also structural differences in parties' overall voting agreement. Some parties show high agreement with many parties across the political spectrum, while others maintain more exclusive voting patterns. Certain parties tend to function as intermediaries in parliamentary voting, cooperating with a wide range of political actors (Dal Maso et al., 2014). In Dutch politics, centrist parties like CDA and D66 have historically functioned as such intermediaries. Conversely, populist parties tend to isolate, avoiding compromises required for broad voting coalitions (Otjes & Louwerse, 2015b). Hence, the following hypothesis is proposed:

> H2.4: Some parties are more likely to agree with many other parties.

Relationships between parties can also be understood through broader structural patterns. One such pattern is group formation: parties that frequently vote together do so within larger groups rather than isolated pairs. This reflects a familiarity mechanism, where two parties both agreeing with a third signals ideological compatibility and reduces uncertainty (Bäck et al., 2024), increasing the likelihood they will also agree. As this repeats across parties, cohesive groups of cooperation emerge. The following hypothesis is proposed:

> H2.5: Parties are more likely to agree on motions when they both often agree with the same third party.

RQ2 will be answered through modelling an Exponential Random Graph Model (ERGM), using terms depicted in Table 1.

Table 1: Hypotheses and ERGM Terms for Study 2

Hypothesis	ERGM Term	Motivation
H2.1: Parties with similar ideologies on the left-right spectrum are more likely to agree on motions.	`absdiff(LeftVSRight)`	The term absdiff measures how differences between node (i.e. party) attributes impact tie formation, capturing how differences in ideology impact voting agreement.
H2.2: Parties that have often been in a coalition together are more likely to agree on motions.	`edgecov(coalitioncount)`	The edgecov term measures how ties in another network impact tie formation. In the context of this research, a network is used with a count variable for how many times parties have been in a coalition together as edge weight.
H2.3: Parties who frequently co-sponsor motions tend to agree more with each other.	`edgecov(cosponsor_count)`	The edgecov term adds a dyadic predictor to the model. Here, a matrix counting how often each pair of parties co-sponsored motions is used to test whether co-sponsorship frequency increases voting agreement.

Hypothesis	ERGM Term	Motivation
H2.4: Some parties are more likely to agree with many other parties.	`kstar(3)`	The kstar(3) term captures the tendency for some parties to form a wider pattern of cooperation by agreeing with many others. Specifically, 3-star reflects parties that maintain multiple voting agreements at once, identifying those that function as broad intermediaries.
H2.5: Parties are more likely to agree on motions when they both often agree with the same third party.	`gwesp`	Gwesp captures the tendency for parties with shared agreement for a third party to vote the same.

This research contributes to existing work by analysing how parties collaborate through agreement on motions, treating these patterns as a network and examining their structure alongside traditional measures such as ideology and coalition experience. It advances understanding of Dutch parliamentary voting patterns by identifying key intermediary parties, and provides empirical evidence about heterogeneity in party agreement patterns. Furthermore, it provides insights about how voting agreement is impacted by elections and coalition formation.

Section 2 details the data used for this research and Section 3 presents the adopted research rationale. Section 4 presents the findings of both studies, and Section 5 summarises the answers to the research questions and offers directions for future work.

2 Dataset

2.1 Data Sources and Collection

We combine multiple datasets to examine Dutch parliamentary voting patterns.

2.1.1 Primary Data

Primary data are voting records scraped from the Open Data Portal of the Dutch House of Representatives (Tweede Kamer der Staten-Generaal, 2024) via automated Python API queries. The portal integrates four sources from which we only use Parlis (motions and voting results). We extracted votes from two periods: *November 22, 2022 - November 21, 2023* (pre-election) and *July 5, 2024 - July 4, 2025* (post-formation), filtering for in-Favour/Against votes only.

We construct undirected party co-voting networks where nodes are parties and edge weights w_{ij} represent the number of motions on which parties i and j cast the same vote (both in favour or both against). Table 2 shows raw voting statistics.

Table 2: Raw Voting Data by Period

Metric	Pre_Election	Post_Formation
Duration (days)	364	365
Total Votes	81,223	78,745
Unique Motions	4,758	5,009
Active Parties	18	16
Votes per Motion	17.1	15.7

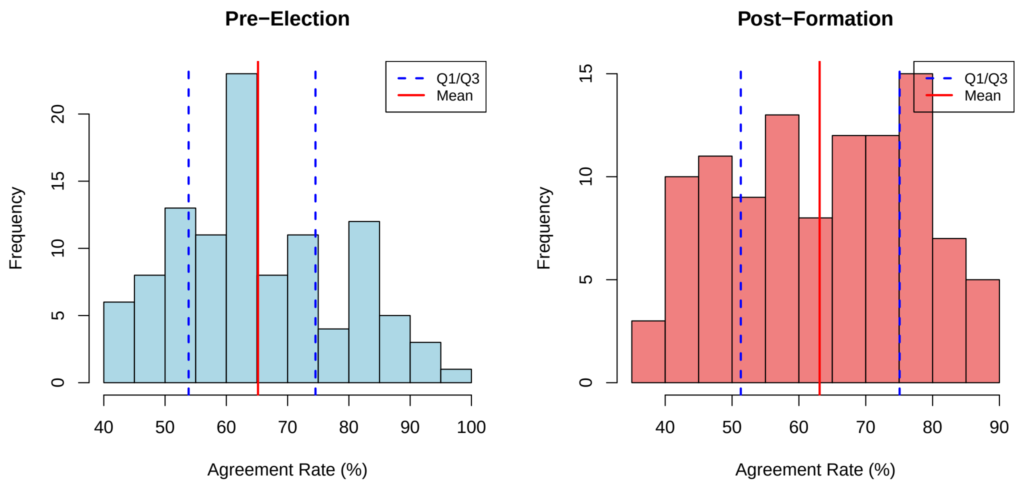
Both studies exclude parties absent or non-functional during the analysis period: Omtzigt (independent MP), BIJ1 (lost representation after 2023), BVNL (no voting activity), and 50PLUS (dissolved with only 2 votes pre-election). For Study 1, both networks include the same 17 parties, as QAP compares corresponding node positions across networks. Study 2 removes two additional parties per period (pre: GroenLinks-PvdA and NSC; post: GroenLinks and PvdA), as GroenLinks and PvdA merged after the election and NSC only emerged post-election, resulting in 15 parties per network.

For network preparation, raw weights are converted to agreement rates as fractions between 0 and 1, by dividing by the number of motions in each period:

$$w_{ij}^{\text{normalized}} = \frac{\text{Agreement Count}_{ij}}{\text{Total Motions}}$$

Based on the distribution of agreement rates in both networks (Figure 1), two thresholds were evaluated for binarizing the networks that will be evaluated by the ERGMs: the mean and the third quartile (Q3). The mean captures broad relationships by including party pairs that agree above average, whilst Q3 retains only the strongest cooperation patterns.

Figure 1: Agreement Rate Distributions by Period. Rates are expressed as percentage of total motions in each period.



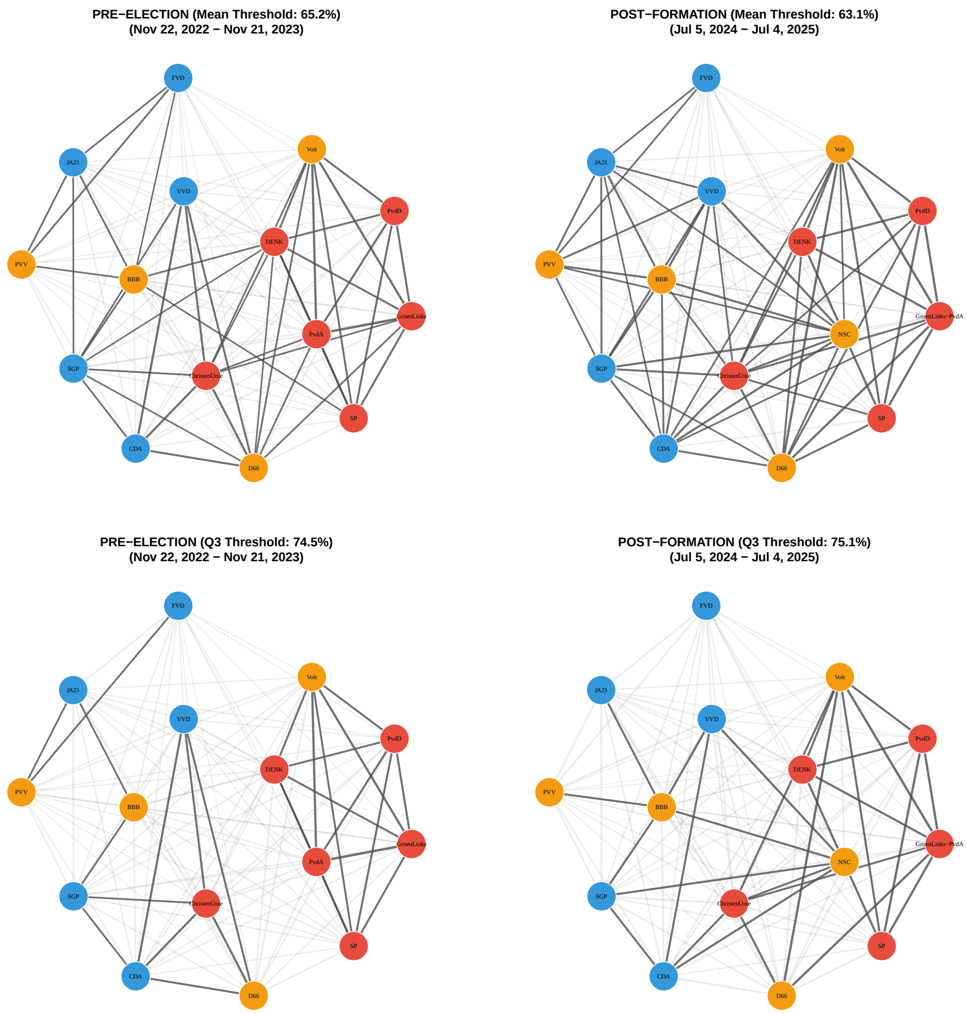
From a theoretical perspective, the Q3 threshold better captures meaningful political relationships by focusing on high-agreement edges. Therefore, we selected Q3 for the final ERGM analysis, while the mean threshold serves as a robustness check to assess whether observed patterns generalize across different threshold definitions.

Figure 2 shows the resulting network structures. The network summaries in Table 3 indicate that Q3 networks mainly differ in transitivity (*0.89* pre-election vs. *0.61* post-formation).

Table 3: Study 2 Network Structure by Threshold (Binarized)

Metric	Pre (Mean 63.9%)	Pre (Q3 74.5%)	Post (Mean 61.3%)	Post (Q3 74.9%)
Nodes (parties)	15	15	15	15
Edges	48	27	57	27
Density	0.46	0.26	0.54	0.26
Transitivity	0.68	0.89	0.74	0.61
Mean Degree	6.4	3.6	7.6	3.6
Isolates	0	0	0	1

Figure 2: Party Voting Networks by Period and Threshold. Darker edges indicate agreements above the threshold. Blue nodes represent right-wing parties, orange nodes represent centrist parties, and red nodes represent left-wing parties.



2.1.2 Supplementary Data for Study 2

Supplementary data include:

1. Ideological positions from Kieskompas 2023 (ProDemos and Kieskompas, 2023), mapped to left-right scales (-1 to +1).
2. Co-sponsorship relationships scraped from the same API we used to scrape voting records.
3. Coalition experience manually collected from parlement.com (Parlement.com, n.d.a), recording historical coalition frequencies between parties.

More details about the data extraction methodology can be found in Appendix B.

The Co-sponsorship and coalition experience variables are captured as networks, with separate networks created for the pre-election and post-formation periods. Table 4 provides summary statistics of the co-sponsorship networks. Coalition experience is captured by a network with 15 edges (range 1-6, mean = 1.9), with CDA-VVD being the pair with the highest coalition experience. Both co-sponsorship and coalition experience are included as edge attributes in the voting agreement networks, ideological positions are included as node attributes.

Table 4: Co-Sponsorship Network Statistics by Period

Metric	Pre_Election	Post_Formation
Total Edges	122	91
Mean Co-Sponsorship Count	31.4	52.1
Max Co-Sponsorship Count	359	385
Network Density	0.642	0.479

2.2 Data Usefulness and Potential Biases

These data are well-suited for studying how voting agreement changes across the electoral cycle. The timestamps enable direct comparison of pre- and post-election behaviour. Agreement is directly measured through recorded votes, and combining these with ideology, coalition experience, and co-sponsorship allows testing which factors shape parliamentary cooperation.

A potential bias is the ideological measurement error from extracting Kieskompas coordinates (Bakker et al., 2015; Louwerse & Otjes, 2012), this however likely affects all parties equally and is mitigated by using ideology as a predictor rather than outcome. Temporal validity concerns (2023 ideology data vs. 2024 voting) are minimal as established party positions remain relatively stable (Gross & Debus, 2021).

3 Research Rationale

The first study investigates whether voting agreement patterns among Dutch political parties differ before elections compared to the period after coalition formation. To compare these two networks, we consider the Quadratic Assignment Procedure (QAP) and Multiple Regression QAP (MRQAP).

QAP is the appropriate method for this research because it tests whether two networks show structural similarity by calculating the correlation between their adjacency matrices. The procedure repeatedly permutes node labels (party names) to generate a null distribution used to determine whether the observed correlation differs from what would occur by chance. MRQAP extends QAP by including predictor variables to explain edge formation, but this is unnecessary for RQ1, which focuses on whether the overall network structure changed rather than *why* specific relationships exist.

If the networks are uncorrelated (i.e., the correlation is not statistically different from zero), this indicates that voting agreement patterns in one period do not predict patterns in the other period, suggesting that cooperation structures re-organize between the pre-election and post-formation periods.

The second study investigates the factors driving voting agreement patterns between parties. Binary Exponential Random Graph Models (ERGMs) enable us to test how party-level attributes (ideology), dyadic relationships (co-sponsorship and coalition patterns), and structural network effects (transitivity, degree distribution) influence voting agreement between two parties, making an ERGM suitable for the second study.

A bipartite ERGM (parties x motions) was also considered, but not selected because it would model explicit voting behaviours per motion, rather than combined voting agreement, thereby failing to address our research question. Additionally, the resulting network (~75,000 possible edges resulting from 15 parties x ~5000 motions, see Table 2) would be too computationally heavy and incompatible with our party-level dyadic attributes like coalition experience and co-sponsorship.

Additionally, a weighted approach using a Generalized ERGM (GERGM) was explored. Several GERGM specifications were implemented but failed to converge reliably, likely caused by the small network size (15 parties) and computational demands of modelling continuous edge weights. Moreover, the GERGM framework restricts the range of structural terms that can be specified, limiting our ability to model mechanisms relevant for answering RQ2. Given these constraints, binarized ERGMs provide the most suitable and robust modelling strategy for Study 2.

4 Results

In this section, the findings of both Study 1 and Study 2 are presented.

4.1 Results Study 1

To assess whether voting agreement on motions between Dutch parties changes before elections compared to the period after coalition formation, we compared the two weighted voting-agreement networks (generated before binarizing, see Section 2) using a Quadratic Assignment Procedure (QAP) correlation test.

This test generated a permutation distribution representing correlations expected under the null hypothesis of no relationship between the networks. Table 5 summarizes the test results, and Figure 3 visualizes the permutation distribution of 1000 simulated correlations. The observed Pearson correlation between the networks is -0.118 (r = -0.1184753).

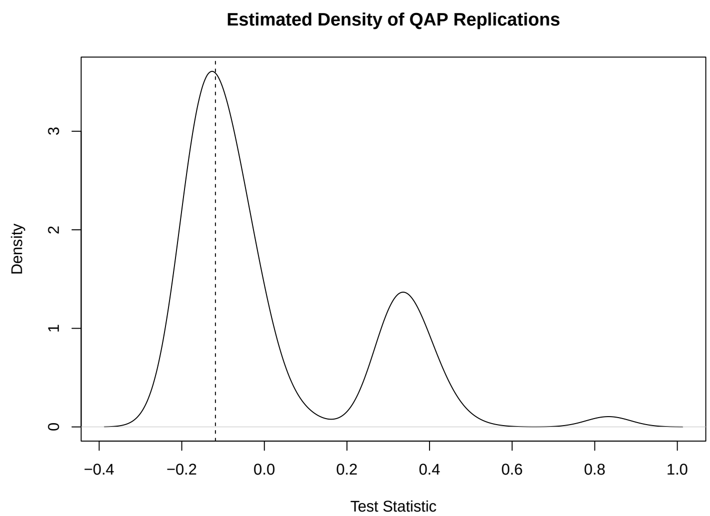
Table 5: QAP Test Results Summary

Statistic	Value
Observed Correlation (r)	-0.1185
Replications	1000
p-value (observed)	0.634
p-value (observed)	0.366
Permutation Distribution:	
Mean	0.0150
Median	-0.0841
Min	-0.2348
Max	0.8602

The two-tailed p-values indicate that the observed correlation of -0.118 is not statistically significant for a significance level of $\alpha = 0.05$, and therefore no conclusions about the direction of the correlation can be made. Specifically, 37% of randomly permuted networks showed correlations equal to or lower than the observed value (p = 0.37), while 63% showed correlations equal to or higher (p = 0.63). Both p-values exceed the 5%, indicating that the observed correlation is well within the range of values expected by random chance alone.

Figure 3 visualizes this result: the dashed vertical line marking the observed correlation falls within the central portion of the permutation distribution, not in its tails where significant results would appear. This indicates that voting agreement patterns in one period do not predict patterns in the other. The lack of correlation suggests that cooperation structures re-organized between the two periods, supporting H1.1.

Figure 3: Permutation Distribution of QAP Test.



4.2 Results Study 2

In this section, the final ERGMs selected for both the pre-coalitions and post-coalition networks are presented. Results are discussed per model.

This study starts off with four networks as discussed in Section 2: pre-election and post-formation, using both the mean and Q3 thresholds. They were tested for convergence to check generalizability; all models converged. We use the **Q3 threshold** for the final analysis, as the mean produced larger AIC/BIC shifts, while Q3 gave more stable results – as can be seen in Table 6.

Table 6: Results of converging tests for pre- and post network with a binarization threshold of either the mean, or Q3

Term	Pre-Q3	Pre-Mean	Post-Q3	Post-Mean
edges	-2.146*	-3.392**	-1.167	-5.776*
absdiff.left_right	-0.704	-1.154	-2.409*	-2.448*
edgecov.coalition_matrix_pre	-0.387	0.088	—	—
edgecov.cosponsor_matrix_pre	0.041**	0.028*	—	—
kstar3	-0.311***	-0.082**	-0.262**	-0.089***
gwesp.fixed.0.7	1.562***	2.219***	1.379***	4.332***
edgecov.coalition_matrix_post	—	—	0.019	-0.154
edgecov.cosponsor_matrix_post	—	—	0.021**	0.029**
AIC	59.5	83.9	68.8	67.8
BIC	75.4	99.8	84.7	83.7
Log Likelihood	-23.7	-36.0	-28.4	-27.9

*Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$*

4.2.1 Pre-election Network Results

The final ERGM for the pre-election network was chosen after comparing several stepwise model builds. Exogenous terms (*edgecov(coalition)*, *edgecov(cosponsor)*, and *absdif(left_right)*) were added first. The results (Appendix C.1) showed that the model with all three terms performed best on AIC, BIC, and log likelihood. Next, the endogenous terms *kstar(3)* and *gwesp(0.70)* were added one by one. These results (Appendix C.2) showed that including both terms gave the best overall performance.

The selected model was then refined by testing gwesp decay values from 0.70 to 0.85 in steps of 0.05. Results are shown in Appendix C.3. The AIC/BIC and log-likelihood stayed stable across these settings. Based on the best performing Goodness of Fit (GOF) and Markov Chain Monte Carlo (MCMC), a decay of 0.75 was chosen as optimal. We therefore proceed with this in the final pre-election model, Appendix D provides full model settings. This model yields an AIC of 58.28, a BIC of 74.21, and a log-likelihood of -23.14 (see highlighted row in Appendix C.3).

4.2.1.1 MCMC Diagnostics

Appendix E shows that the MCMC traces for most terms are stable, fluctuating around constant central values. The edges, ideological distance, and cosponsorship terms show no drift, and their density plots are unimodal and well behaved. However the coalition term performs notably worse. Its trace shows wide, irregular swings and fails to settle into a stable range, indicating poor mixing and reduced reliability. Most components perform well, but the poor coalition term should be considered when interpreting its effect.

4.2.1.2 Goodness-of-fit

The GOF plots (Appendix F) show that the model captures some broad structural tendencies of the pre-election network, but several discrepancies remain.

The model underestimates nodes both with low and high degrees. It also underrepresents edges with multiple shared partners, indicating limited local clustering by generating fewer closed triads than observed. In addition, the minimum geodesic distance distribution shows that the model predicts too many short paths, resulting in an overly connected network. Overall, model fit is limited, and results should therefore be interpreted with caution.

4.2.1.3 Model Term Estimates

The ERGM estimates are expressed on a log scale. To make these results easier to interpret, estimates were converted into probabilities using the following formula:

$$p = \frac{e^{\text{estimate}}}{1 + e^{\text{estimate}}}$$

Table 7 presents these ERGM estimates for the pre-election network. In interpreting these results, $\alpha = 0.05$ is chosen as a threshold for statistical significance.

Table 7: Results Pre-election ERGM

Term	Estimate	Probability	Odds Ratio	Std. Error	z value	Pr(>|z|)	Signif
edges	-2.148	0.105	0.117	0.972	-2.209	0.027	*
absdiff.left_right	-0.674	0.338	0.510	0.737	-0.914	0.361	
edgecov.coalition matrix_pre	-0.389	0.404	0.678	0.711	-0.547	0.585	
edgecov.cosponsor matrix_pre	0.041	0.510	1.042	0.015	2.815	0.005	**
kstar3	-0.315	0.422	0.729	0.088	-3.582	0.000	***
gwesp.fixed.0.75	1.522	0.821	4.580	0.339	4.492	0.000	***

Firstly, the negative and statistically significant *edges* term (p = 0.027) shows that the probability of any two parties agreeing on a motion (under the Q3 binarization threshold) is low (10.5%). This indicates that voting agreement is generally unlikely in this network.

The first term, the *absdiff(left_right)*, is not statistically significant (p=0.388). This indicates that ideological proximity does not systematically increase voting agreement in the pre-election period, providing no support for H2.1.

Also the *edgecov(coalition_matrix_pre)* term is not statistically significant (p=0.584), offering no empirical support for H2.2. This result should be interpreted with caution due to the terms unstable MCMC diagnostics

The *edgecov(cosponsor_matrix_pre)* term estimate is positive and statistically significant ($\beta = 0.041$, p = 0.008), though the effect is small. The predicted probability is about 51.0%, meaning that parties that often co-sponsor motions are only slightly more likely to agree on motions. The small effect gives limited support for H2.3.

The *kstar(3)* term is statistically significant and negative ($\beta = -0.315$, $p < 0.001$). This indicates that high-degree nodes are less common than expected under a random baseline. The probability of 42.2% shows that ties increasing a party's degree are moderately unlikely. H2.4 is therefore not supported in this network.

The *gwesp(0.75)* term shows a positive and statistically significant effect ($\beta = 1.5126$, $p < 0.001$) indicates a strong transitive effect. The corresponding probability shows that when parties both agree with the same third party, then they are 82.1% more likely to agree with each other.This provides support for H2.5.

4.2.2 Post-Coalition Formation Network Results

For the final specification of the ERGM for the post-formation network, all terms remain included, with the same Q3 binarisation threshold and *gwesp* decay of 0.75.

As in the pre coalition analysis, additional experiments were conducted using hierarchical model building in Appendix G.1 and Appendix G.2 and gwesp decay values ranging from 0.70 to 0.85 (Appendix G.3). Although some of these specifications produced slightly improved MCMC or GOF results, the original (pre-election) decay setting was retained to ensure comparability between the pre- and post-network models. The final post-formation ERGM specification is reported in Appendix H, with results shown in Table 8. This model yields an AIC of 68.63, a BIC of 84.55, and a log-likelihood of −28.31.

4.2.2.1 MCMC Diagnostics

The MCMC diagnostics (Appendix I) show that the MCMC-sampler behaves adequately for nearly all parameters in the post-coalition model. The traces for edges, ideological distance, and cosponsorship stay close to stable values and show no drift, with clean and unimodal densities. The coalition term also mixes much better than in the pre-coalition model and stays within a narrow, stable band. The endogenous terms *kstar(3)* and *gwesp(0.75)* display similarly regular traces and densities.

Overall, the diagnostics suggest proper convergence and more reliable estimates than in the pre-coalition model.

4.2.2.2 Goodness-of-fit

The GOF plots (Appendix J) show that the model fits the post-coalition network reasonably well. The model slightly underrepresents nodes at the extremes of the degree distribution and predicts too many short paths, resulting in a somewhat more connected network than observed. These deviations are limited, and the model provides a solid basis for interpreting the ERGM results in the post-coalition analysis.

4.2.2.3 Model Term Estimates

Table 8 presents the ERGM estimates for the post-coalition network. The estimates are converted to probabilities using the estimate formula. Significance is again evaluated at $\alpha = 0.05$.

Table 8: Results Post-formation ERGM

Term	Estimate	Probability	Odds Ratio	Std. Error	z value	Pr(>|z|)	Signif
edges	-1.094	0.251	0.335	0.861	-1.270	0.204	
absdiff.left_right	-2.436	0.080	0.088	0.964	-2.527	0.012	*
edgecov.coalition matrix_post	0.012	0.503	1.012	0.287	0.042	0.967	
edgecov.cosponsor matrix_post	0.021	0.505	1.022	0.007	3.223	0.001	**
kstar3	-0.265	0.434	0.767	0.083	-3.209	0.001	**
gwesp.fixed.0.75	1.321	0.789	3.748	0.346	3.822	0.000	***

The *edges* term is negative but not statistically significant ($\beta = -1.094$, p = 0.204). This indicates that there is no strong evidence for a change in the baseline likelihood of an agreement tie after applying the Q3 threshold, although the estimated probability of ties forming remains at 25.1%.

Unlike for the pre-election period, the *absdiff(left_right)* term is statistically significant ($\beta = -2.436$, p = 0.011). The corresponding probability of 8.0% shows that, when two parties are ideologically far apart, their chances of voting in agreement are very low, highlighting a strong role of ideological similarity in shaping post-coalition voting patterns. This provides support for H2.1.

The *edgecov(coalition_matrix_post)* term remains statistically non-significant ($\beta = 0.0119$, p = 0.97), offering no evidence that past coalition participation predicts agreement after the election. Given the now stable MCMC diagnostics, the absence of a significant effect appears substantive rather than a result of model instability. Thus, H2.2 is not supported in the post-coalition network.

The *cosponsorship* term retains a positive and statistically significant estimate ($\beta = 0.0213$, p = 0.0013). However, the estimate is again small, translating in a modest near-baseline probability of 50.3%. Co-sponsorship thus plays only a modest role, offering limited support for H2.3 across both periods.

Just as for the pre-election network, the *kstar(3)* term is negative and statistically significant ($\beta = -0.265$, p = 0.001), with a similar probability 43.4%, again showing that high-degree nodes are less common than expected under a random baseline. This disproves H2.4.

The *gwesp(0.75)* term remains positive and significant with a large estimate ($\beta = 1.321$, p < 0.001). Parties that often agree with the same third party are again more likely to agree with each other, in this period with a probability of 78.9%. This shows that clustering in agreement persists, and supports H2.5 in both networks.

5 Discussion & Conclusion

This project researched how Dutch political parties cooperate through parliamentary voting and how these patterns change across the 2023 - 2024 electoral cycle. The research was divided into two studies. The research question of Study 1 was:

> RQ1: Do Dutch political parties show different patterns in voting agreement with respect to motions in the period before elections compared to the period after coalition formation?

We built on this research with a secondary study answering the following research question:

> RQ2: How do ideological similarity, shared coalition experience, and structural voting patterns influence inter-party agreement on parliamentary motions?

Combining these questions allows us to uncover which factors drive voting agreement between parties, and how these patterns shift with political context. This is crucial for understanding actual collaboration in parliament and determining which factors can help formation of stable majority coalitions in the fragmented Dutch political landscape.

Study 1 examined whether the overall pattern of voting differs between the year before the 2023 elections and the year after the new coalition was formed. With a QAP correlation test, we found that the observed similarity between the two networks is no greater than what would be expected by random chance. Combined with descriptive differences in mean tie strength (see Table 3) and the changes visible in the network plots (see Figure 2), this supports our hypothesis that Dutch political parties show different patterns of voting agreement before elections compared to after coalition formation.

Study 2 used ERGMs to investigate the mechanisms behind these patterns. We observed strong clustering effects in both periods, reflected in positive and significant *gwesp* terms. This shows that parties tend to agree in groups rather than in pairs, regardless of differing political context surrounding the elections. However, the MCMC diagnostics differed: the post-formation model converged more easily and showed better fit, while the pre-election model was harder to estimate. This suggests that agreement before the election is more mixed and unpredictable and becomes more stable after coalition formation.

The role of ideology was different for the two periods. Before the election, ideological similarity did not significantly influence voting agreement. This indicates that strategic behavior or coalition signalling might overshadow the impact of ideological proximity in the pre-election phase voting patterns. In the period after coalition formation, ideological distance showed a significant negative effect on agreement, meaning that ideologically similar parties are more likely to vote the same on motions. This shift could imply that ideological alignment becomes more influential once the electoral competition is over and governing begins. This may also be caused by the government/opposition divide potentially making ideological positions more binding.

Other factors showed weaker or more nuanced effects. Coalition history did not significantly increase or decrease voting agreement in either period. This suggests that previous cooperation in government does not necessarily translate into consistent mutual support on motions. Moreover, the coalition term complicated model convergence and degraded GOF, likely because only a small and stable subset of parties participates in coalitions, leaving too little structural variation for ERGM estimation.

Similarly, the results show no evidence that parties act as broad intermediaries who systematically agree with many others. Instead, the network structure in both periods disfavors such central actors and agreement tends to form within structured clusters rather than revolving around a few widely connected parties. This shows how fragmentation suppresses the intermediary role that center parties provided in the past, forming a political structure with co-voting groups instead of broad cross-party agreements.

Finally, co-sponsorship had a modest but positive effect in both periods, which suggests that legislative collaboration encourages agreement but is not a dominant driver of voting behavior. The signals of co-sponsorship, therefore, indicate some cooperation but explain only a small share of the overall structure of the parliamentary agreement.

Together, the two studies show that Dutch parliamentary agreement is shaped by differences between political phases together with the underlying network structure. Elections and coalition formation cause differences in agreement patterns, potentially due to parties' efforts to differentiate themselves and position strategically during campaigns, whilst remaining more ideology-driven during actual governing. At the same time, the network mechanism of clustering appears stable across both periods. Hence, co-voting groups emerge not only from external political factors like ideology and coalition history, but also from already existing interactions and dynamics within the parliament.

These findings have several important implications for different stakeholders. For parliamentarians, recognising that ideological alignment becomes more important after formation can help anticipate voting behavior during governing periods. Besides, awareness of strong clustering effects enables better expectations about coalition support on key issues. Furthermore, this study offers academic insights relevant to political scientists studying legislative behavior by showing how cooperation develops across the electoral phases. Journalists and policy analysts can also use such insights to better explain coalition negotiations,voting behaviour, and potential legislative bottlenecks.

5.1 Future Research

A question that remains unaddressed in this research is which exact political events are driving the observed shifts in voting agreement. Future work could analyse continuous time-series data rather than two snapshots to better identify when structural shifts occur and thus which events drive them.

In addition, this study does not consider the content of motions as a potential driver of voting agreement. All motions are treated uniformly, ignoring how policy areas might affect co-voting patterns. Future research could classify motions by topic to examine these effects, and a bipartite ERGM would be well-suited for this purpose, as it allows information about both motions and parties to be modelled simultaneously.

Furthermore, this research focuses on only one coalition formation cycle. It would be valuable to examine whether similar shifts in voting agreement occur in other formation cycles. Future research could replicate this study for the 2025 elections to assess whether the before-and-after pattern observed here recurs in Dutch parliamentary politics or is specific to the 2023-2024 cycle. This would clarify whether changes in voting agreement are structurally linked to elections and coalition formation or depend on the specific political context of each cycle.

5.2 Concluding

To conclude, this study showed that cooperation in the Dutch parliament changes over time and cannot be explained by ideology alone. Elections and coalition formation transform patterns of agreement, while underlying patterns, especially parties' tendency to agree in groups, remain stable. Understanding these dynamics is essential to interpret parliamentary behavior and offers insights into how political coalitions could evolve within the increasingly fragmented political landscape.

6 Technology statement student(s)

During the preparation of this work, we used ChatGPT in order to improve phrasing of certain words and formulations in writing the report. The tool was also used to translate text initially written in Dutch. After using this tool/service, Anne, Vera, Loes, Max, Roos and Guido always carefully evaluated the validity of the tool's outputs and edited the content as needed. As a consequence, we take full responsibility for the content of this work.

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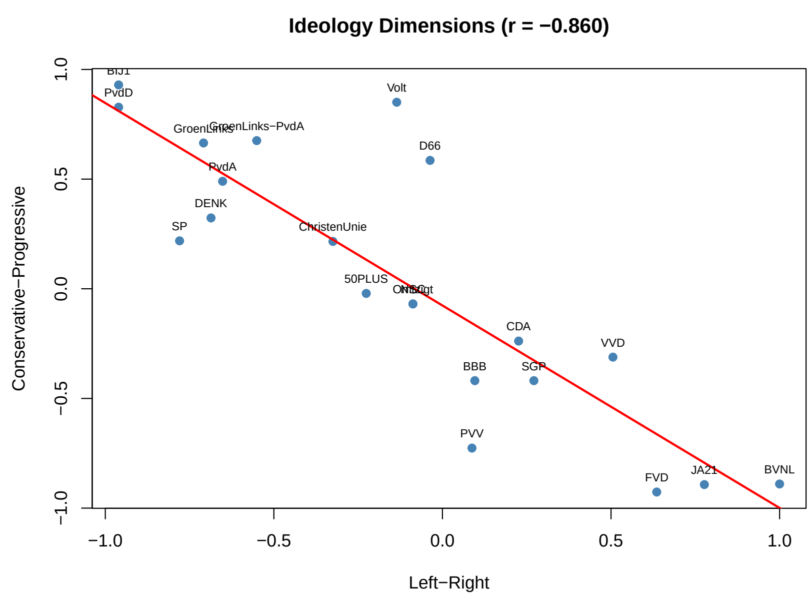
8 Appendix

8.1 A: Correlation left-right vs. progressive-conservative

Ideological positions from Kieskompas show strong correlation between left-right and conservative-progressive dimensions (r = -0.860), as illustrated in Figure 4, indicating substantial overlap. This finding validates the theoretical concern raised in the introduction that the two dimensions may be too closely intertwined. We therefore use only the left-right dimension to avoid multicollinearity.

Figure 4: Ideology Dimensions Correlation



This correlation was obtained with the following code in R:

```
# Pearson correlation between ideology dimensions
pearson_test <- stats::cor.test(ideology_data$left_right,
                                 ideology_data$conservative_progressive,
                                 method = "pearson")

# Scatterplot
plot(ideology_data$left_right, ideology_data$conservative_progressive,
     xlab = "Left-Right", ylab = "Conservative-Progressive",
     main = sprintf("Ideology Dimensions (r = %.3f)", pearson_test$estimate),
     pch = 19, col = "steelblue")
```

```r
abline(lm(conservative_progressive ~ left_right, data = ideology_data),
       col = "red", lwd = 2)

text(ideology_data$left_right, ideology_data$conservative_progressive,
     labels = ideology_data$party, pos = 3, cex = 0.7)
```

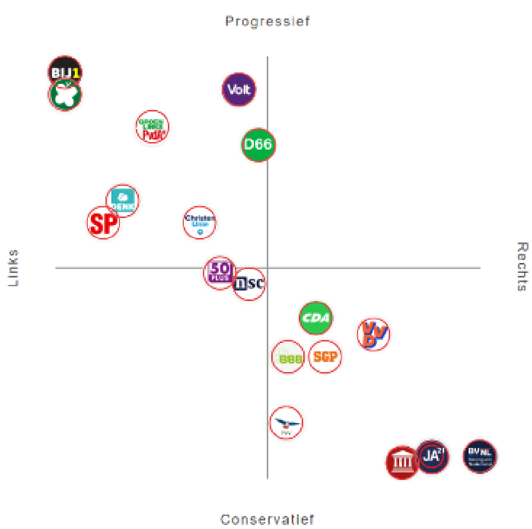
8.2 B: Supplementary Data Collection

8.2.1 Ideological Position Data Extraction

To capture the political positions of Dutch parties across the ideological spectrum, we relied on data from Kieskompas (ProDemos and Kieskompas, 2023), a research organization dedicated to analyzing political opinions and party positioning.

Since Kieskompas does not publicly release the underlying coordinate data, we extracted numerical values from their published visualizations using plot digitization software. The primary data source was the 2023 election visualization (Figure 5). However, the 2023 data included GroenLinks-PvdA as a merged entity, while our pre-election analysis period (2022-2023) required separate coordinates for GroenLinks and PvdA. We therefore supplemented the 2023 data with coordinates for these two parties from previous Kieskompas election visualizations.

Figure 5: Kieskompas 2023 Election Visualization (Source)

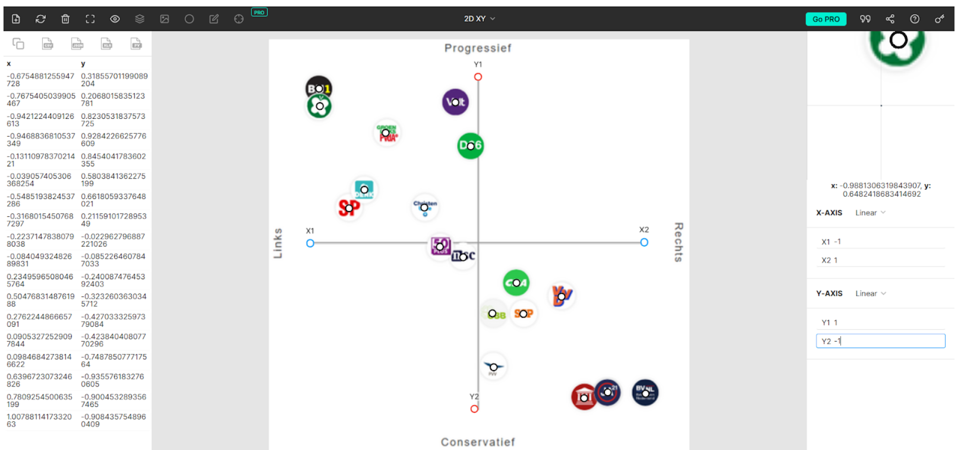


Coordinate extraction was performed using PlotDigitizer (plotdigitizer.com), a web-based tool for extracting numerical data from graph images. The digitization process involved:

1. Uploading the Kieskompas visualization image
2. Calibrating the x-axis (left-right dimension) and y-axis (progressive-conservative dimension) using known reference points
3. Manually selecting each party logo's center point to extract coordinates
4. Exporting the coordinate pairs to CSV format

Figure 6 shows the digitization interface with calibrated axes and extracted party positions. The final dataset contains coordinates for 21 parties on both ideological dimensions, which were then rescaled to the range [-1, +1] for use in our analysis.

Figure 6: Plot Digitization Process using PlotDigitizer.com



8.2.2 Coalition Experience Data Collection

To capture historical coalition patterns between Dutch political parties, we collected data on coalition formations from Parlement.com (Parlement.com, n.d.a), an authoritative source documenting all Dutch government formations since 1945.

The data collection process was entirely manual and involved:

1. Reviewing each coalition formation listed on https://www.parlement.com/kabinetsformaties-sinds-1945
2. Identifying which parties participated in each coalition government within the 20-year window
3. Recording each unique party pair that served together in a coalition
4. Counting the frequency of co-participation for each party pair across all coalitions

This dyadic coalition count data was structured as an undirected edge list (party A, party B, number of coalitions together) and stored in CSV format.

8.3 C: Hierarchial Building for the Q3 Thresholded Pre-election Network

This appendix presents the stepwise model building process for the pre-election Q3 network, testing different combinations of exogenous and endogenous terms.

During the model development process, numerous model specifications were tested and systematically documented to identify the optimal configuration. Figure 7 shows the complete testing overview for the pre-election network.

Figure 7: Model Testing Overview for Pre-Election Network

Pre										
Converged?	Threshold	Terms						Results		
		Edges	*Left_right*	*coalition*	*cosponsor*	*gwesp(0.x)*	*kstar(3)*	*AIC*	*BIC*	*Log liklihood*
Converged	0.65	Edges	Left_right***			gwesp(0.1)	kstar(3)	104.9	115.51	-48.45
Converged	0.65	Edges	Left_right**			gwesp(0.3)**	kstar(3)*	98.55	98.55	-45.28
Converged	0.65	Edges	Left_right**			gwesp(0.5)***	kstar(3)*	94.43	105.05	-43.21
Converged	0.65	Edges	Left_right***	coalition		gwesp(0.1)	kstar(3)*	91.46	104.73	-40.73
Converged	0.65	Edges	Left_right**	coalition		gwesp(0.3)**	kstar(3)*	85.69	98.96	-37.84
Converged	0.65	Edges	Left_right**	coalition		gwesp(0.5)***	kstar(3)**	81.39	94.66	-35.7
Converged	0.65	Edges	Left_right*		cosponsor***	gwesp(0.1)	kstar(3)**	71.27	84.54	-30.63
Converged	0.65	Edges	Left_right*		cosponsor***	gwesp(0.3)	kstar(3)**	69.31	82.58	-29.65
Converged	0.65	Edges	Left_right		cosponsor***	gwesp(0.5)*	kstar(3)**	67.41	80.4	-28.57
Converged	0.65	Edges	Left_right*	coalition	cosponsor***	gwesp(0.1)	kstar(3)**	72.48	88.41	-30.24
Converged	0.65	Edges	Left_right*	coalition	cosponsor**	gwesp(0.3)	kstar(3)**	70.36	86.28	-29.18
Converged	0.65	Edges	Left_right	coalition	cosponsor **	gwesp(0.5)***	kstar(3)**	67.96	83.89	-27.98
Converged	0.68	Edges	Left_right***			gwesp(0.1)	kstar(3)*	103.72	114.34	-47.86
Converged	0.68	Edges	Left_right**			gwesp(0.3)**	kstar(3)*	96.08	106.69	-44.04
Converged	0.68	Edges	Left_right**			gwesp(0.5)***	kstar(3)*	90.37	100.98	-41.18
Converged	0.68	Edges	Left_right***	coalition*		gwesp(0.1)	kstar(3)*	94.48	107.75	-42.24
Converged	0.68	Edges	Left_right***	coalition*		gwesp(0.3)**	kstar(3)**	87.72	100.99	-38.86
Converged	0.68	Edges	Left_right**	coalition		gwesp(0.5)***	kstar(3)**	82.36	95.63	-36.18
Converged	0.68	Edges	Left_right*		cosponsor***	gwesp(0.1)	kstar(3)**	70.63	83.9	-30.32
Converged	0.68	Edges	Left_right		cosponsor***	gwesp(0.3)*	kstar(3)**	67.34	80.61	-28.67
Converged	0.68	Edges	Left_right		cosponsor***	gwesp(0.5)**	kstar(3)***	63.57	76.84	-26.79
Converged	0.68	Edges	Left_right*	coalition	cosponsor***	gwesp(0.1)	kstar(3)**	71.68	87.6	-29.84
Converged	0.68	Edges	Left_right	coalition	cosponsor***	gwesp(0.3)	kstar(3)**	68.73	84.66	-28.37
Converged	0.68	Edges	Left_right	coalition	cosponsor***	gwesp(0.5)**	cosponsor***	65.03	80.96	-26.52
Converged	0.7	Edges	Left_right***			gwesp(0.1)*	kstar(3)	102.63	113.25	-47.32
Niet converged	0.7	Edges	Left_right			gwesp(0.3)	kstar(3)	-	-	-
Converged	0.7	Edges*	Left_right**			gwesp(0.5)***	kstar(3)*	86.47	97.09	-39.24
Converged	0.7	Edges	Left_right**	coalition		gwesp(0.1)*	kstar(3)*	90.36	103.63	-40.18
Converged	0.7	Edges	Left_right**	coalition		gwesp(0.3)**	kstar(3)*	82.95	96.22	-36.48
Converged	0.7	Edges	Left_right**	coalition		gwesp(0.5)***	kstar(3)**	77.29	90.56	-33.64
Converged	0.7	Edges	Left_right		cosponsor***	gwesp(0.1)	kstar(3)**	69.83	83.1	-29.92
Converged	0.7	Edges	Left_right*		cosponsor***	gwesp(0.3)*	kstar(3)**	65.1	78.37	-27.55
Converged	0.7	Edges	Left_right		cosponsor***	gwesp(0.5)**	kstar(3)***	60.06	73.33	-25.03
Converged	0.7	Edges	Left_right	coalition	cosponsor***	gwesp(0.1)	kstar(3)**	70.8	86.73	-29.4
Converged	0.7	Edges	Left_right	coalition	cosponsor**	gwesp(0.3)*	kstar(3)**	66.61	82.53	-27.31
Converged	0.7	Edges	Left_right	coalition	cosponsor***	gwesp(0.5)**	kstar(3)**	61.62	77.55	-24.81

8.3.1 Testing Exogenous Terms

Table 9: Stepwise ERGM: Testing Exogenous Terms for Pre-Election Q3 Network

Term	Model 1	Model 2	Model 3	Model 4
edges	0.44	-1.10	0.25	-1.28
absdiff.left_right	-2.79***	-2.46**	-3.02***	-2.37*
edgecov.cosponsor_matrix_pre	—	0.04***	—	0.04**
edgecov.coalition_matrix_pre	—	—	1.15*	-0.47
AIC	105.3	81.7	95.9	83.2
BIC	110.6	89.7	103.9	93.9
Log Likelihood	-50.6	-37.9	-44.9	-37.6

*Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$*

8.3.2 Testing Endogenous Terms

Table 10: Stepwise ERGM: Adding Endogenous Terms for Pre-Election Q3 Network

Term	Model 1	Model 2	Model 3	Model 4
edges	-1.28	0.24	-2.82***	-2.15*
absdiff.left_right	-2.37*	-2.04*	-2.07*	-0.70
edgecov.cosponsor_matrix_pre	0.04**	0.06***	0.03*	0.04**
edgecov.coalition_matrix_pre	-0.47	-0.51	-0.37	-0.39
kstar3	—	-0.24*	—	-0.31***
gwesp.fixed.0.7	—	—	0.93**	1.56***
AIC	83.2	77.8	76.7	59.5
BIC	93.9	91.0	90.0	75.4
Log Likelihood	-37.6	-33.9	-33.4	-23.7

*Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$*

8.3.3 Testing GWESP Decay Parameters

Table 11: Stepwise ERGM: Testing GWESP Decay Parameters for Pre-Election Q3 Network

Term	Model 1	Model 2	Model 3	Model 4
edges	-2.15*	-2.15*	-2.14*	-2.14*

Table 11: Stepwise ERGM: Testing GWESP Decay Parameters for Pre-Election Q3 Network

Term	Model 1	Model 2	Model 3	Model 4
absdiff.left_right	-0.70	-0.67	-0.66	-0.61
edgecov.cosponsor_matrix_pre	0.04**	0.04**	0.04**	0.04**
edgecov.coalition_matrix_pre	-0.39	-0.39	-0.39	-0.40
kstar3	-0.31***	-0.32***	-0.32***	-0.32***
gwesp.fixed.0.7	1.56***	—	—	—
gwesp.fixed.0.75	—	1.52***	—	—
gwesp.fixed.0.8	—	—	1.48***	—
gwesp.fixed.0.85	—	—	—	1.44***
AIC	59.5	**58.3**	57.3	56.2
BIC	75.4	**74.2**	73.2	72.2
Log Likelihood	-23.7	**-23.1**	-22.6	-22.1

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

8.4 D: Final Model Definition for the Pre-election Network

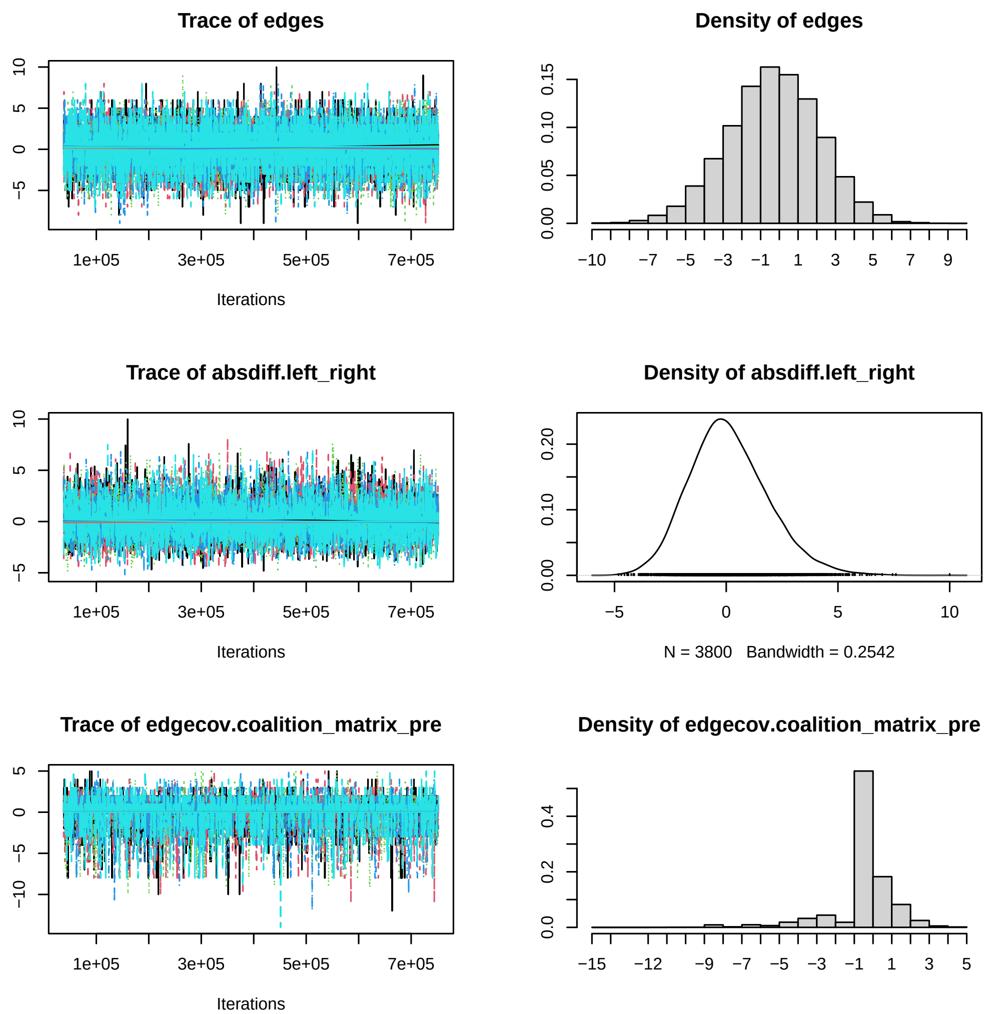
The final pre-election ERGM was estimated using the following specification:

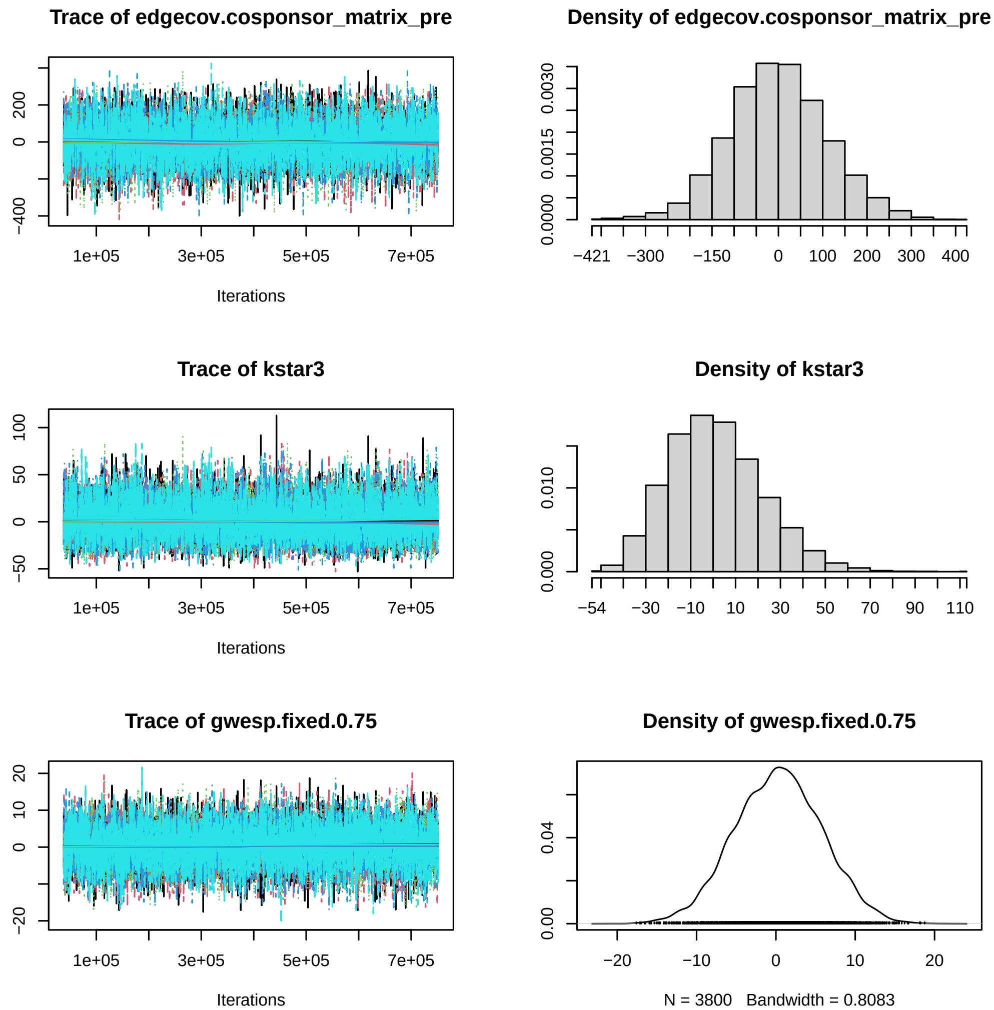
```
# ERGM control parameters
ergm_control <- ergm::control.ergm(
  MCMC.burnin = 7000,
  MCMC.samplesize = 20000,
  MCMC.interval = 1500,
  seed = 1234,
  MCMLE.maxit = 40,
  parallel = 5,
  parallel.type = "PSOCK",
  MCMC.prop = ~sparse + .triadic
)

# Final Models (Q3 threshold, decay 0.75)
FinalModel_pre_q3 <- ergm::ergm(
  net_pre_q3 ~
    edges + absdiff("left_right") +
    edgecov(coalition_matrix_pre) + edgecov(cosponsor_matrix_pre) +
    kstar(3) + gwesp(0.75, fixed = TRUE),
  control = ergm_control
)
```

8.5 E: MCMC Diagnostics for Final Pre-Election Model

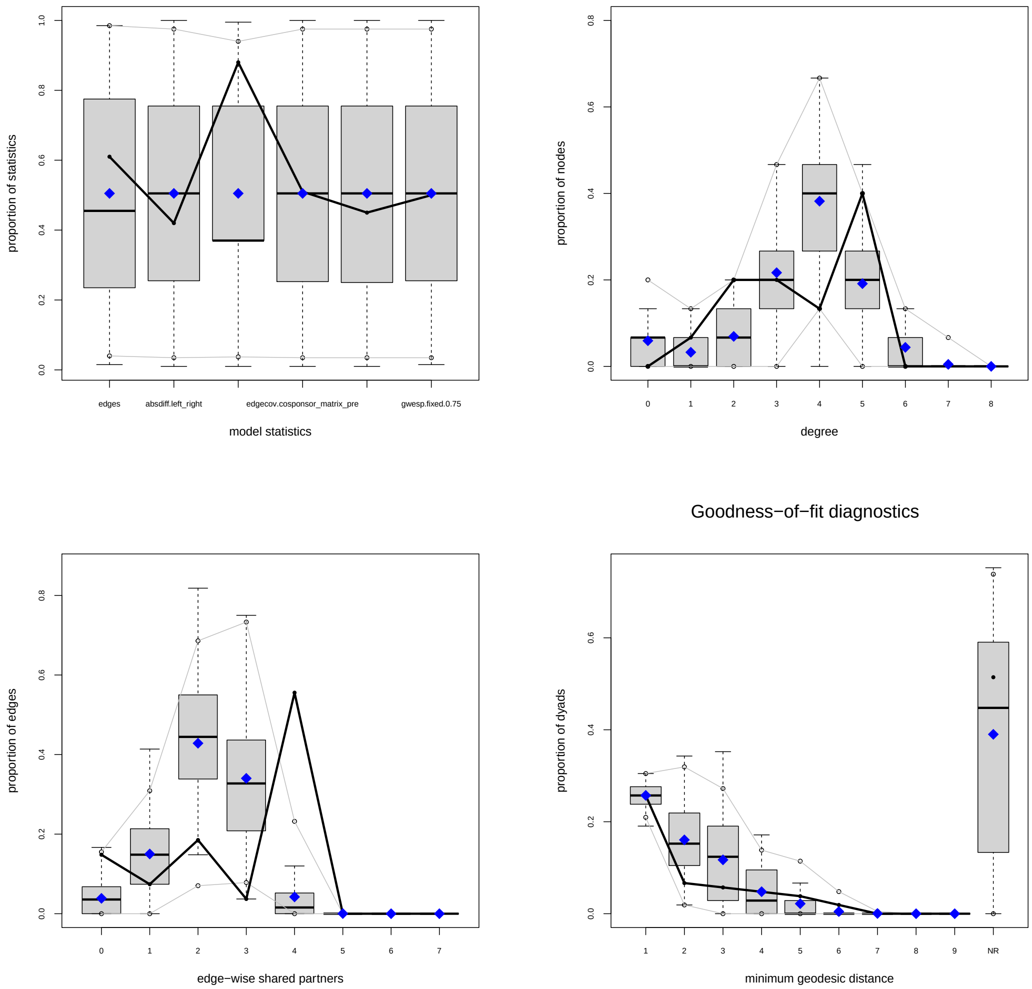
This appendix presents the Markov Chain Monte Carlo (MCMC) diagnostics for the final pre-election Q3 model.




Trace of edgecov.cosponsor_matrix_pre
Iterations
Density of edgecov.cosponsor_matrix_pre
Trace of kstar3
Iterations
Density of kstar3
Trace of gwesp.fixed.0.75
Iterations
Density of gwesp.fixed.0.75
N = 3800   Bandwidth = 0.8083

8.6 F: Goodness-of-Fit Diagnostics for Final Pre-Election Model

This appendix presents the goodness-of-fit (GOF) diagnostics for the final pre-election Q3 model.



8.7 G: Hierarchial Building for the Q3 Thresholded Post-formation Network

This appendix presents the stepwise model building process for the post-formation Q3 thresholded network. The final ERGM for the post-formation network was chosen after comparing several stepwise model builds.

During the model development process, numerous model specifications were tested and systematically documented to identify the optimal configuration. Figure 8 shows the complete testing overview for the post-formation network.

Figure 8: Model Testing Overview for Post-Formation Network

Post										
Converged?	Threshold	Terms						Results		
		Edges	*Left_right*	*coalition*	*cosponsor*	*gwesp(0.x)*	*kstar(3)*	*AIC*	*BIC*	*Log liklihood*
Niet converged	0.65	Edges	Left_right			gwesp(0.1)	kstar(3)	-	-	-
Niet converged	0.65	Edges	Left_right			gwesp(0.3)	kstar(3)	-	-	-
Niet converged	0.65	Edges	Left_right			gwesp(0.5)	kstar(3)	-	-	-
Niet converged	0.65	Edges	Left_right	coalition		gwesp(0.1)	kstar(3)	-	-	-
Niet converged	0.65	Edges	Left_right	coalition		gwesp(0.3)	kstar(3)	-	-	-
Converged	0.65	Edges***	Left_right**	coalition		gwesp(0.5)***	kstar(3)***	70.88	84.15	-30.44
Converged	0.65	Edges**	Left_right		cosponsor***	gwesp(0.1)**	kstar(3)**	71.15	84.42	-30.58
Converged	0.65	Edges*	Left_right		cosponsor***	gwesp(0.3)**	kstar(3)***	62.19	75.46	-26.09
Converged	0.65	Edges*	Left_right		cosponsor***	gwesp(0.5)***	kstar(3)***	57.09	70.36	-23.55
Converged	0.65	Edges	Left_right	coalition	cosponsor**	gwesp(0.1)*	kstar(3)***	67.44	83.36	-27.72
Converged	0.65	Edges*	Left_right	coalition	cosponsor**	gwesp(0.3)**	kstar(3)***	61.04	76.97	-24.52
Converged	0.65	Edges**	Left_right	coalition	cosponsor **	gwesp(0.5)***	kstar(3)***	55.84	71.76	-21.92
Converged	0.68	Edges	Left_right***			gwesp(0.1)	kstar(3)	110.4	121.01	-51.2
Converged	0.68	Edges*	Left_right**			gwesp(0.3)**	kstar(3)*	98.17	108.79	-45.09
Converged	0.68	Edges**	Left_right**			gwesp(0.5)***	kstar(3)**	87.85	98.47	-39.93
Converged	0.68	Edges	Left_right**	coalition		gwesp(0.1)	kstar(3)	98.6	111.87	-44.3
Converged	0.68	Edges*	Left_right**	coalition		gwesp(0.3)**	kstar(3)*	87	100.27	-38.5
Converged	0.68	Edges**	Left_right**	coalition		gwesp(0.5)***	kstar(3)***	76.48	89.75	-33.24
Converged	0.68	Edges	Left_right*		cosponsor***	gwesp(0.1)	kstar(3)**	78	91.27	-34
Converged	0.68	Edges	Left_right*		cosponsor***	gwesp(0.3)**	kstar(3)**	70.66	83.93	-30.33
Converged	0.68	Edges*	Left_right		cosponsor***	gwesp(0.5)***	kstar(3)***	62.5	75.77	-26.25
Converged	0.68	Edges	Left_right*	coalition	cosponsor***	gwesp(0.1)	kstar(3)**	79.97	95.89	-33.98
Converged	0.68	Edges	Left_right*	coalition	cosponsor***	gwesp(0.3)**	kstar(3)**	72.71	88.63	-30.35
Converged	0.68	Edges*	Left_right	coalition	cosponsor***	gwesp(0.5)***	kstar(3)***	64.44	80.36	-26.22
Converged	0.7	Edges	Left_right***			gwesp(0.1)*	kstar(3)	106.13	116.75	-49.07
Converged	0.7	Edges*	Left_right**			gwesp(0.3)***	kstar(3)**	94.47	105.08	-43.23
Converged	0.7	Edges**	Left_right**			gwesp(0.5)***	kstar(3)**	87.2	97.82	-39.6
Converged	0.7	Edges	Left_right**	coalition		gwesp(0.1)*	kstar(3)	93.1	106.37	-41.55
Converged	0.7	Edges*	Left_right**	coalition		gwesp(0.3)**	kstar(3)**	81.9	95.17	-35.95
Converged	0.7	Edges**	Left_right**	coalition		gwesp(0.5)***	kstar(3)***	74.35	87.62	-32.17
Converged	0.7	Edges	Left_right*		cosponsor***	gwesp(0.1)	kstar(3)**	66.53	79.8	-28.26
Converged	0.7	Edges	Left_right		cosponsor***	gwesp(0.3)**	kstar(3)***	60.11	73.38	-25.05
Converged	0.7	Edges	Left_right		cosponsor***	gwesp(0.5)***	kstar(3)***	54.94	68.21	-22.47
Converged	0.7	Edges	Left_right*	coalition	cosponsor***	gwesp(0.1)	kstar(3)**	68.34	84.26	-28.17
Converged	0.7	Edges	Left_right	coalition	cosponsor***	gwesp(0.3)**	kstar(3)***	62.03	77.95	-25.02
Converged	0.7	Edges	Left_right	coalition	cosponsor***	gwesp(0.5)***	kstar(3)***	56.69	72.61	-22.34

8.7.1 Stepwise Model Building - Exogenous Predictors

Table 12: Stepwise ERGM: Adding Exogenous Predictors for Post-Formation Q3 Network

Term	Model 1	Model 2	Model 3	Model 4
edges	0.682	-0.505	0.511	-0.505
absdiff.left_right	-3.562***	-3.612**	-3.530***	-3.605**
edgecov.cosponsor_matrix_post	—	0.021***	—	0.020***
edgecov.coalition_matrix_post	—	—	0.463	0.041
AIC	101.3	82.7	100.2	84.6
BIC	106.6	90.6	108.1	95.3
Log Likelihood	-48.7	-38.3	-47.1	-38.3

*Note: *** p < 0.001; ** p < 0.01; * p < 0.05*

8.7.2 Stepwise Model Building - Endogenous Predictors

Table 13: Stepwise ERGM: Adding Endogenous Predictors for Post-Formation Q3 Network

Term	Model 1	Model 2	Model 3	Model 4
edges	-0.505	0.561	-1.711*	-1.167
absdiff.left_right	-3.605**	-3.426**	-3.123**	-2.409*
edgecov.cosponsor_matrix_post	0.020***	0.029***	0.015**	0.021**
edgecov.coalition_matrix_post	0.041	0.031	0.033	0.019
kstar3	—	-0.152	—	-0.262**
gwesp.fixed.0.7	—	—	0.635*	1.379***
AIC	84.6	81.7	82.2	**68.8**
BIC	95.3	95.0	95.5	**84.7**
Log Likelihood	-38.3	-35.9	-36.1	**-28.4**

*Note: *** p < 0.001; ** p < 0.01; * p < 0.05*

8.7.3 Testing GWESP Decay Parameters

Table 14: Stepwise ERGM: Testing GWESP Decay Parameters for Post-Formation Q3 Network

Term	Model 1	Model 2	Model 3	Model 4
edges	-1.167	-1.094	-1.034	-0.975
absdiff.left_right	-2.409*	-2.436*	-2.464*	-2.482*
edgecov.cosponsor_matrix_post	0.021**	0.021**	0.021**	0.021**
edgecov.coalition_matrix_post	0.019	0.012	0.017	0.015
kstar3	-0.262**	-0.265**	-0.267**	-0.269**
gwesp.fixed.0.7	1.379***	—	—	—
gwesp.fixed.0.75	—	1.321***	—	—
gwesp.fixed.0.8	—	—	1.269***	—
gwesp.fixed.0.85	—	—	—	1.222***
AIC	68.8	**68.6**	68.4	68.3
BIC	84.7	**84.6**	84.4	84.2
Log Likelihood	-28.4	**-28.3**	-28.2	-28.1

*Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$*

8.8 H: Final Model Definition for the Post-formation Network

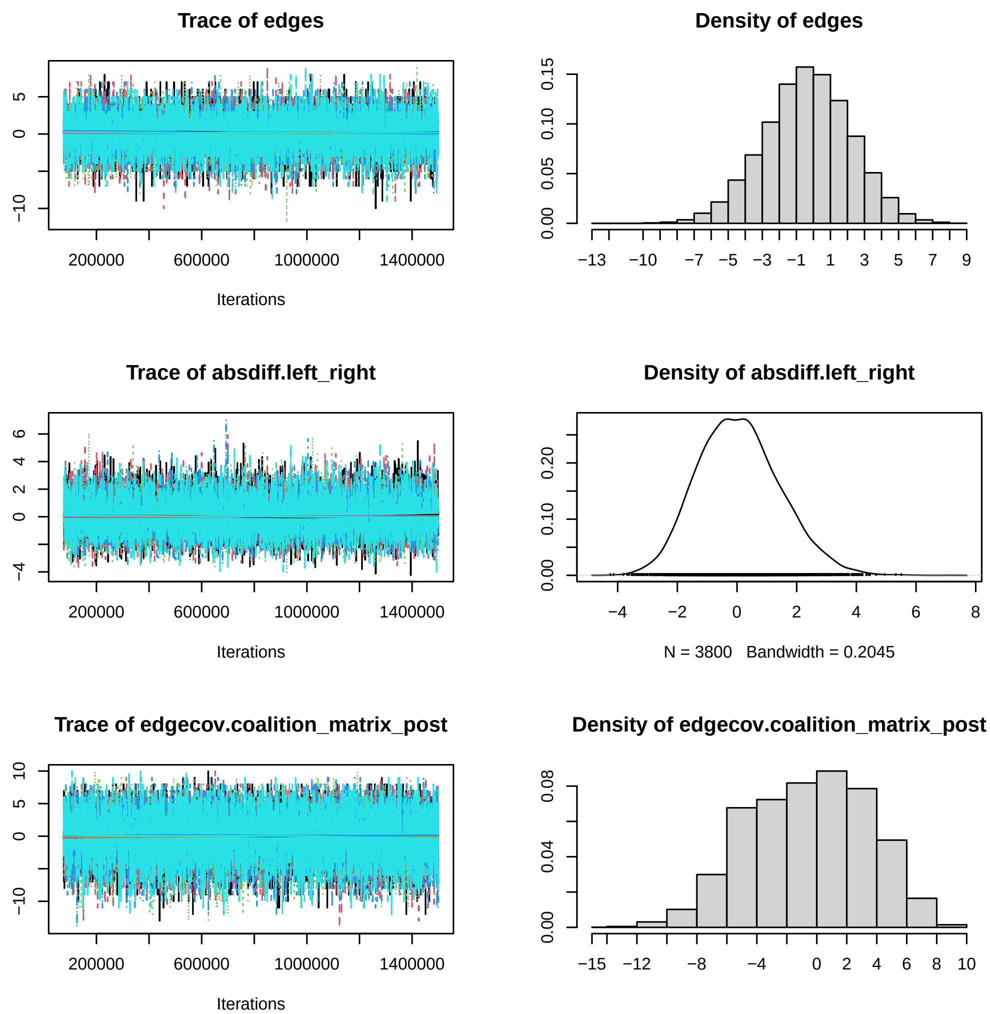
The final post-formation ERGM was estimated using the following specification:

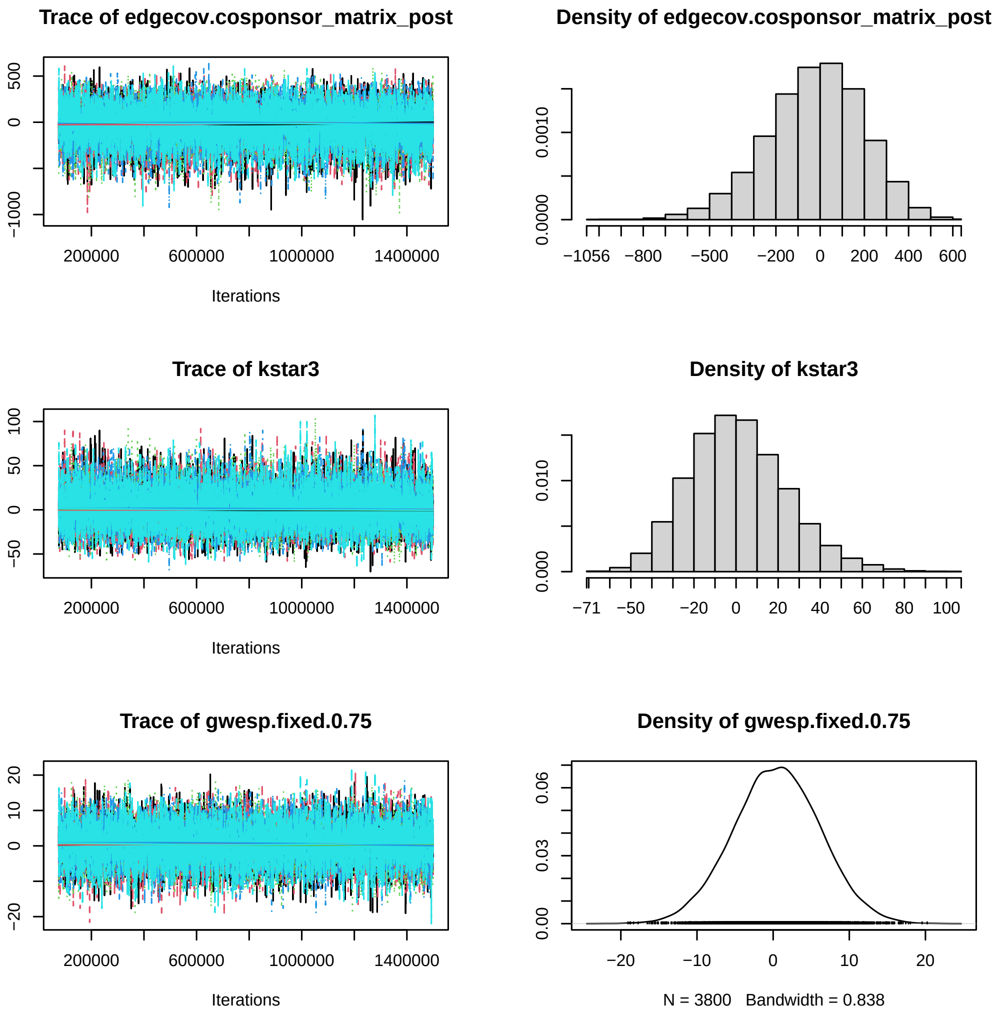
```
# ERGM control parameters
ergm_control <- ergm::control.ergm(
  MCMC.burnin = 7000,
  MCMC.samplesize = 20000,
  MCMC.interval = 1500,
  seed = 1234,
  MCMLE.maxit = 40,
  parallel = 5,
  parallel.type = "PSOCK",
  MCMC.prop = ~sparse + .triadic
)

# Final post-formation model (Q3 threshold, decay 0.75)
FinalModel_post_q3 <- ergm::ergm(
  net_post_q3 ~
    edges + absdiff("left_right") +
    edgecov(coalition_matrix_post) + edgecov(cosponsor_matrix_post) +
    kstar(3) + gwesp(0.75, fixed = TRUE),
  control = ergm_control
)
```

8.9 I: MCMC Diagnostics for Final Post-formation Model

This appendix presents the Markov Chain Monte Carlo (MCMC) diagnostics for the final post-formation Q3 model.




Trace of edgecov.cosponsor_matrix_post
Density of edgecov.cosponsor_matrix_post
Trace of kstar3
Density of kstar3
Trace of gwesp.fixed.0.75
Density of gwesp.fixed.0.75
Iterations
Iterations
Iterations
200000
600000
1000000
1400000
500
0
−1000
0.0000
0.0010
−1056
−800
−500
−200
200
400
600
100
50
−50
0.000
0.010
−71
−20
20
40
60
80
20
10
−20
0.00
0.03
0.06
−10
N = 3800   Bandwidth = 0.838

8.10 J: Goodness-of-Fit Diagnostics for Final Post-formation Model

This appendix presents the goodness-of-fit (GOF) diagnostics for the final post-formation Q3 model.